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Evaluating health-care waste treatment technologies using a hybrid multi-criteria decision making model

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ABSTRACT

Health-care waste (HCW) management is a high priority public health and environmental concern particularly in developing countries. The decision to select an optimal technology for the disposal of HCW is a complicated multi-criteria decision analysis problem involving both qualitative and quantitative factors. Evaluating HCW treatment technologies may be based on imprecise information or uncertain data. Moreover, there can be significant dependence and feedbacks between the different dimensions and criteria. However, most existing decision models for HCW cannot capture these complex interrelationships. In response, this paper proposes a novel hybrid multi-criteria decision making (MCDM) model by integrating the 2-tuple DEMATEL technique and fuzzy MULTIMOORA method for selection of HCW treatment alternatives. It makes use of modified 2-tuple DEMATEL for obtaining the relative weights of criteria and fuzzy MULTIMOORA for assessing the alternatives according to each criterion. Specifically, an empirical case in Shanghai, one of the largest cities in China, is provided to illustrate the potential of the new model. Results show that the proposed framework for evaluating HCW treatment technologies is effective and provides meaningful implications for engineering designers to refer.

Contents

1. Introduction

Nowadays health-care waste (HCW) management has become a crucial public health and environmental issue particularly in developing countries as a direct result of rapid industrialization and population growth. Improper waste management can cause

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Table 1
Classification of health-care wastes [13].

Waste category	Components
Tissues	Human or animal pathological wastes, including tissues, organs, blood, pus, and body parts and fluids
Infectious waste	Blood, blood products and objects that are contaminated with them; microbiological laboratory wastes; quarantine wastes; dialysis wastes; used surgical operating clothes; infectious organ pieces, blood and anything contaminated with these materials
Sharp objects	Needles, syringes, broken glass, blades, and other items that could cause a cut or puncture
Chemical waste	Hazardous chemicals, heavy metal containing wastes, pharmaceutical wastes, amalgam wastes, gynotoxic wastes, gentoxic wastes
Medicine waste	Common medicines that are expired or are no longer required or are discarded; other medicines discarded that could cause cancers or genetic diseases; the discarded vaccine products

environmental pollution, unpleasant odors, and growth of insects, rodents and worms; it may lead to transmission of diseases like typhoid, cholera, and hepatitis through injuries from sharps contaminated with human blood [1,2]. For improving HCW management, several previous investigations and studies in various contexts have indicated the importance of appropriate techniques for waste treatment [3–6]. In many developing countries, however, medical wastes are still handled and disposed of together with other domestic wastes, thus posing significant health risks to municipal workers, the general population and the environment [7–10]. According to a survey of the World Health Organization (WHO) on HCW management in 22 developing countries, the proportion of health care institutions with inappropriate waste disposal methods was between 18% and 64% [11]. HCW can be defined as any waste generated by health-care facilities and laboratory facilities operating in hospital settings that is considered to be potentially hazardous to human health [12]. It includes sharps, body fluids, dressing materials, surgically removed body tissues, chemicals, pharmaceuticals, medical devices and radioactive materials [9]. According to the Medical Waste Category Regulation of China [13], wastes from health-care institutions are classified into five main groups as presented in Table 1. Although proper management of HCW includes a number of activities, this paper focuses on the treatment and final disposal of the medical wastes.

When selecting treatment technologies for HCWs, decision makers have to take into account various important criteria or factors simultaneously for successful outcomes and optimal decisions. During the evaluation process, a large number of factors such as capital cost, waste residuals, release with health effects, reliability, treatment effectiveness, occupational hazards and public acceptance are often included [3,4]. They often contradict and even conflict each other [14]. Each treatment technology has different performance for each evaluation attribute. There is no HCW disposal alternative which satisfies all the relevant criteria. Therefore, the evaluation of HCW treatment technologies, which considers the need to trade-off multiple conflicting criteria with the involvement of a group of experts, can be viewed as a complex multi-criteria decision making (MCDM) problem. To ease out the HCW treatment technology selection procedure and make the right decision, a systematic and efficient approach is required.

Up to now, a lot of mathematical techniques have been developed and applied to solve HCW management problems arising from various countries and regions. The main problem associated with the existing decision analysis methods is that most of them cannot handle the analysis of complicated and interrelated relationships among different hierarchical levels of criteria. However, the decision to determine the most suitable HCW disposal technology requires a decision model that performs just that analysis. Moreover, in many real-life situations, the judgments of decision makers are often vague and it is difficult to indicate preference with an exact numerical value. That is, decision makers often tend to assess the ratings of alternatives and the relative weights of criteria in the problem by using linguistic terms rather than numerical values. To respond to these necessities, this paper aims to develop a novel hybrid MCDM model that combines 2-tuple DEMATEL technique with the fuzzy MULTIMOORA method to overcome the limitations of conventional decision models, which can be used to help engineering designers analyze the interrelationships in the selection of HCW treatment technologies. Specifically, a case study in Shanghai, one of the largest cities in China, is utilized to illustrate the computational procedure and potential benefits of the proposed framework.

The remainder of this paper is organized as follows: a review of the relevant literature on HCW management practices is given in Section 2. A hybrid MCDM model combining 2-tuple DEMATEL and fuzzy MULTIMOORA for assessment of HCW treatment technologies is developed in Section 3. In Section 4, an empirical case conduced in Shanghai, China is presented to demonstrate the new decision framework. Finally, conclusions and future research directions are provided in Section 5.

2. Literature review

In the literature, many investigations and studies have been conducted in various contexts to assess HCW management practices. Mostly, these studies used the prepared questionnaires, field research and personnel interviews to survey health-care institutions generating the wastes. For example, Patwary et al. [9] undertook a survey of medical waste management in Dhaka, the capital city of Bangladesh to investigate the potential risks to environmental safety, particularly for the individuals who are working with medical waste. Gai et al. [15] investigated the current status of HCW management at different levels of health care facilities in Binzhou District, Shandong Province after the implementation of national regulations and standards in China and Yong et al. [12] conducted a comprehensive inspection survey to analyze and evaluate the present practices of medical waste management in the light of medical waste control regulations in Nanjing, China. Manga et al. [8] presented an evaluation of HCW management systems in Cameroon, based on a survey of five health care facilities in the Southwestern Region of Cameroon in order to identify current practices and areas which require improvement. Ferreira and Teixeira [16] analyzed the HCW management practices in hospitals of the Algarve region, Portugal, and in particular assessed the risk perceptions of, and actual risk to, the healthcare staff working in these hospitals. Abd El-Salam [17] investigated the medical waste management practices used by eight randomly selected hospitals located in El-Beheira Governorate, Egypt and determined the total daily generation rate as well as physico-chemical characteristics of their wastes. Taghipour and Mosaferi [7] conducted a survey to determine the quantity, generation rate, quality, and composition of medical waste generated in the major city northwest of Iran in Tabriz. Birpınar et al. [18] analyzed the present status of medical waste management in the light of the medical waste control regulation in Istanbul, the largest city in Turkey through interviews made with healthcare

services managers. Al-Khatib and Sato [19] assessed HCW management practices currently employed at health care centers in the West Bank- Palestinian Territory and made some recommendations on proper remediation measures and management of HCW.

In other way, to improve HCW management, some studies have focused on the selection of the optimal technique for waste treatment. For instance, Dursun et al. [3] proposed two fuzzy MCDM techniques for the evaluation of HCW treatment approaches, which enable to conduct an analysis based on a multi-level hierarchical structure and to incorporate imprecise data represented as linguistic variables into the analysis. Liu et al. [4] presented a MCDM model based on the fuzzy set theory and VIKOR method for identifying the most suitable HCW disposal alternative, in which linguistic variables were used to assess the ratings and weights for the established criteria and the ordered weighted averaging (OWA) operator was utilized to aggregate individual opinions of decision makers into a group assessment. In [14], a fuzzy multi-criteria group decision making framework for assessing HCW treatment technologies for Istanbul was proposed based on the principles of fuzzy measure and fuzzy integral. The proposed decision approach enables to incorporate imprecise data represented as linguistic variables into the decision analysis. Soares et al. [6] evaluated the performance of different HCW management scenarios for small generators – involving microwaving, autoclave and lime disinfection using a life cycle assessment (LCA) and cost analysis, and indicated that microwave disinfection presents the best eco-efficiency performance and provides a feasible alternative to subsidize the formulation of the policy for small generators of HCW. Karagiannidis et al. [20] assessed the thermal treatment processes of infectious hospital wastes in Central Macedonia, Greece via the analytic hierarchy process (AHP). The AHP and the relevant sensitivity analysis demonstrated that a centralized autoclave or hydroclave plant is the best performing option, depending on the selection and weighing of criteria of the multi-criteria process. Brent et al. [21] combined the AHP technique with a life cycle management (LCM) approach in the context of sustainable development to establish and optimize HCW management systems that minimize infection risks in rural areas of developing countries.

The review of the literature indicates that although the existing methods provide many useful tools for the evaluation of HCW treatment technologies, most of them still lack of capability to explore the relationships among evaluation criteria for more in-depth analysis. In order to help fill the gap, this study proposes a new hybrid MCDM model combining 2-tuple DEMATEL and fuzzy MULTIMOORA to deal with the HCW treatment technology selection problem, aiming at exploring the plausible interrelationships among the considered criteria for making better decision. The modified 2-tuple DEMATEL technique is used to uncover the relationships between criteria and their network structure and then find the influential weights for each dimension and criterion in the evaluation structure; the fuzzy MULTIMOORA method is employed for calculating the robust ranking of the alternatives and identifying the most suitable one for the given problem.

3. A hybrid MCDM model for evaluating HCW technologies

In this section, a hybrid MCDM model based on 2-tuple DEMATEL technique and the fuzzy MULTIMOORA method is presented to address the problem of HCW treatment technology selection with interdependence and feedback among certain criteria. In short, the proposed model for evaluation of HCW disposal alternatives consists of two main stages: (1) constructing the influential relation map (IRM) among the dimensions and criteria and calculating their influential weights by the 2-tuple DEMATEL technique, and (2) ranking and improving the performances of HCW treatment alternatives through the fuzzy MULTIMOORA method. The flowchart of the proposed hybrid MCDM model is schematically shown in Fig. 1.

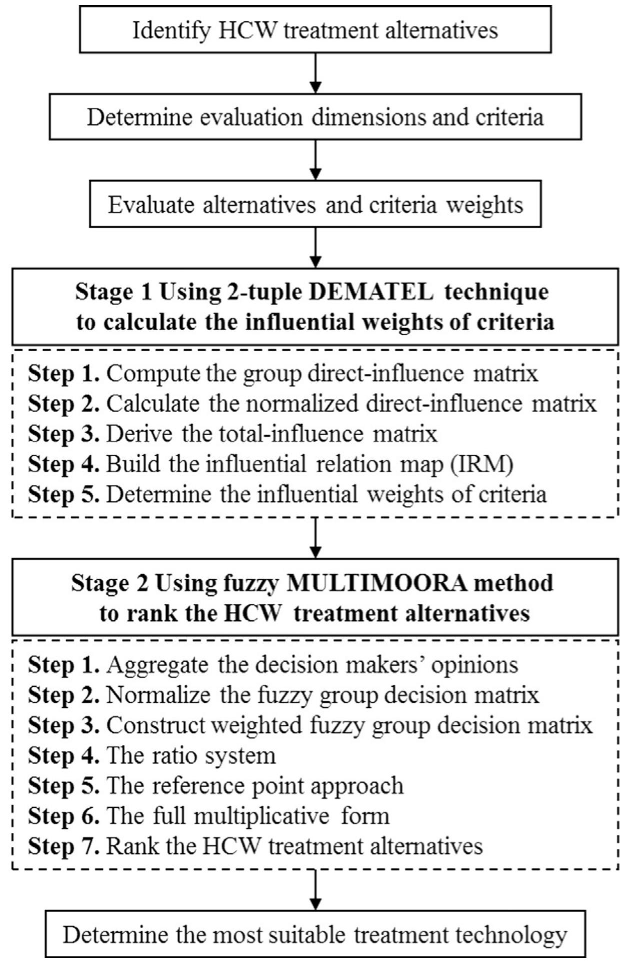

Fig. 1. Flowchart of the proposed hybrid MCDM model.

3.1. The 2-tuple DEMATEL technique

The DEMATEL technique originated from the Geneva Research Centre of the Battelle Memorial Institute is especially pragmatic to visualize the structure of complicated causal relationships and to clarify the essentials of the problems [22]. It is more suitable in real-life applications and has been widely used in various decision making problems [23–29]. The DEMATEL technique can help decision makers and analysts understand the interdependence of variables/criteria through matrices or digraphs and restrict the relations that reflect characteristics within an essential systemic and developmental trend. In this study, a modified 2-tuple DEMATEL approach based on [30] is used to confirm the relationships between the dimensions and criteria of the considered HCW treatment technology evaluation problem to build the IRM among them. In addition, the proposed model also determines the influential weights of criteria by considering the hierarchy of criteria based on the results obtained by the 2-tuple DEMATEL technique.

Step 1. Compute the group direct-influence matrix
Let $F=\{F_1,F_2,\ldots,F_n\}$ be a set of factors, where F_j denotes the jth factor, $j=1,2,\ldots,n$; $E=\{E_1,E_2,\ldots,E_K\}$ be a set of experts, where E_k represents the kth expert, $k=1,2,\ldots,K$. First, experts are

asked to indicate the direct effect that factor F_i has on factor F_j, using a linguistic term set with five labels, i.e.,

$S = \{s_0 = \text{Absolutely no influence (AN)},\ s_1 = \text{Low influence (L)},\ s_2 = \text{Medium influence (M)},\ s_3 = \text{High influence(H)},\ s_4 = \text{Very high influence (VH)}\}$.

Then, the initial direct-influence matrix $Z_k = \left[z_{ij}^k\right]_{n \times n}$ provided by the kth expert E_k can be set up, where $z_{ij}^k \in S$ represents the judgment on the existence of the interrelationship between factors F_i and F_j. After transforming the initial direct-influence matrices into the form of 2-tuples, i.e., $\tilde{Z}_k = \left[\tilde{z}_{ij}^k\right]_{n \times n}, \tilde{z}_{ijk} = \left(z_{ij}^k, 0\right)$, the group direct-influence matrix $\tilde{Z} = \left[\tilde{z}_{ij}\right]_{n \times n}$ can be obtained by using the 2-tuple arithmetic mean operator [31] as given in Eq. (1).

$$\tilde{z}_{ij} = (z_{ij}, \alpha_{ij}) = \Delta\left(\frac{1}{K}\sum_{k=1}^{K}\Delta^{-1}\left(z_{ij}^k, 0\right)\right),\quad z_{ij} \in S, \alpha_{ij} \in [-0.5, 0.5), i, j = 1, 2, \ldots, n. \tag{1}$$

Step 2. Calculate the normalized direct-influence matrix
Using the group direct-influence matrix $\tilde{Z}$, the normalized direct-influence matrix $X = [x_{ij}]_{n \times n}$ is calculated by the following equations:

$$x_{ij} = \frac{\Delta^{-1}(z_{ij}, \alpha_{ij})}{s}, \tag{2}$$

where

$$s = \max\left\{\max_{1 \le i \le n}\sum_{j=1}^{n}\Delta^{-1}(z_{ij}, \alpha_{ij})\right\}. \tag{3}$$

All elements in matrix X are complying with $0 \le x_{ij} < 1, 0 \le \sum_{j=1}^{n} x_{ij} \le 1$ and at least one i such that $\sum_{j=1}^{n}\Delta^{-1}(z_{ij}, \alpha_{ij}) \le s$.

Step 3. Derive the total-influence matrix
Based on the normalized direct-relation matrix X, the total-influence matrix $T = [t_{ij}]_{n \times n}$ can be derived by summing the direct effects and all of the indirect effects using Eq. (4), in which $\boldsymbol{I}$ represents the identity matrix.

$$\mathbf{T} = \mathbf{X} + \mathbf{X}^2 + \mathbf{X}^3 + \cdots + \mathbf{X}^h = \mathbf{X}(\mathbf{I} - \mathbf{X})^{-1},\ \text{when } h \to \infty,\ \mathbf{X}^h = [0]_{n \times n}. \tag{4}$$

Step 4. Build the influential relation map (IRM)
At this step, the sum of the rows and the sum of the columns within the total-influence matrix $\mathbf{T}$ are respectively expressed as the vectors $\mathbf{r}$ and $\mathbf{c}$ using Eqs. (5) and (6).

$$\mathbf{r} = [r_i]_{n \times 1} = \left[\sum_{j=1}^{n} t_{ij}\right]_{n \times 1}, \tag{5}$$

$$\mathbf{c} = [c_j]_{n \times 1} = \left[\sum_{i=1}^{n} t_{ij}\right]_{1 \times n}^{T}. \tag{6}$$

where r_i denotes the sum of the ith row in matrix $\mathbf{T}$ and shows the sum of the direct and indirect effects that factor i has on the other factors. Similarly, c_j denotes the sum of the jth column in matrix $\mathbf{T}$ and shows the sum of direct and indirect effects that factor j has received from the other factors.
Let $i = j$ and $i, j \in \{1, 2, \ldots, n\}$; the horizontal axis vector $(\mathbf{r} + \mathbf{c})$ is then defined by adding $\mathbf{r}$ to $\mathbf{c}$, which illustrates the strength of influences that are given and received of the factor. That is, $(\mathbf{r} + \mathbf{c})$ shows the degree of the central role that the factor plays in the system. Similarly, the vertical axis vector $(\mathbf{r} - \mathbf{c})$ is created by subtracting $\mathbf{c}$ from $\mathbf{r}$, which shows the net effect that the factor contribute to the system. If $(r_j - c_j)$ is positive, then factor j has a net influence on other factors, and if $(r_j - c_j)$ is negative, then factor j is being influenced by other factors on the whole. Finally, an IRM can be acquired by mapping the ordered pairs of $(\mathbf{r} + \mathbf{c},\ \mathbf{r} - \mathbf{c})$, which provides more valuable information for problem solving.
Step 5. Determine the influential weights of criteria
After the DEMATEL confirms the influential relationships between the dimensions and criteria, we use the causal diagram to measure the criteria weights that will be used in the decision making process [22,32]. The relative importance of the criteria is calculated with the following equation:

$$w_j = \left[(r_j + c_j)^2 + (r_j - c_j)^2\right]^{\frac{1}{2}}. \tag{7}$$

Here, Eq. (7) simply denotes the length of the vector starting from the origin to each criterion. The weight of any criterion can be normalized as follows:

$$\overline{w}_j = \frac{w_j}{\sum_{j=1}^{n} w_j}, \tag{8}$$

where $\overline{w}_i$ represents the final criteria weights to be used in the decision making process. Consequently, we can obtain the influential weight for each criterion (i.e., global influential weight) by using the modified 2-tuple DEMATEL approach.

3.2. The fuzzy MULTIMOORA method

The MULTIMOORA method was first proposed by Brauers and Zavadskas [33] as a MCDM method on the basis of multi-objective by ratio analysis (MOORA) [34]. Actually, MULTIMOORA is composed of three parts: ratio system, reference point approach and full multiplicative form. In this way MULTIMOORA becomes the most robust system of multiple objectives optimization as up till now no other approach is known satisfying all conditions of robustness towards multiple objectives optimization and including three or more methods [35]. This method has been widely used in many fields for solving real-world MCDM problems, including climate change mitigation policy assessment [36], building refurbishment element selection [37,38], dynamic schedule execution in manufacturing system [39], sustainable electricity production technology selection [40], and others [41–43].

In the second stage of the proposed MCDM model, the MULTIMOORA is extended to the fuzzy environment to determine the ranking priorities of alternative HCW disposal technologies and identify the best one for the HCW management problem. This

Table 2
Linguistic variables for rating the alternatives.

Linguistic variables	Fuzzy numbers
Very low (VL)	(0, 0, 1)
Low (L)	(1, 2, 3)
Medium low (ML)	(1, 3, 5)
Medium (M)	(3, 5, 7)
Medium high (MH)	(5, 7, 9)
High (H)	(7, 9, 10)
Very high (VH)	(9, 10, 10)

model is very suitable for solving the HCW treatment technology evaluation problem under imprecise and vague information environment. In this paper, it is suggested that the decision makers use linguistic variables to evaluate the ratings of alternatives with respect to each criterion. These linguistic variables can be taken as positive triangular fuzzy numbers as shown in Table 2.

Assuming that a HCW treatment technology selection problem has l decision makers $\mathrm{DM}_k(k=1,2,\ldots,l)$, m alternatives $A_i(i=1,2,\ldots,m)$ and n evaluation criteria $C_j(j=1,2,\ldots,n)$. Then the development of the fuzzy MULTIMOORA method begins with the following matrix form:

$$\tilde{X}^k=\begin{bmatrix}\tilde{x}_{11}^k & \tilde{x}_{12}^k & \cdots & \tilde{x}_{1n}^k\\ \tilde{x}_{21}^k & \tilde{x}_{22}^k & \cdots & \tilde{x}_{2n}^k\\ \vdots & \vdots & \cdots & \vdots\\ \tilde{x}_{m1}^k & \tilde{x}_{m2}^k & \cdots & \tilde{x}_{mn}^k\end{bmatrix},$$

where $\tilde{x}_{ij}^k$ is the rating/performance of alternative A_i with respect to criterion C_j provided by the kth decision maker. In here, the ratings of alternatives are linguistic terms which can be expressed by triangular fuzzy numbers, $\tilde{x}_{ij}^k=\left(x_{ij1}^k,x_{ij2}^k,x_{ij3}^k\right)$. Based upon the aforementioned assumptions or notations, the ranking algorithm of fuzzy MULTIMOORA consists of the following steps:

Step 1. Aggregate the decision makers' opinions
The aggregated fuzzy ratings $\tilde{x}_{ij}$ of alternatives with respect to each criterion can be calculated to construct a fuzzy group decision matrix $\tilde{X}=[\tilde{x}_{ij}]_{m\times n}$ by utilizing the following equation:

$$\tilde{x}_{ij}=(x_{ij1},x_{ij2},x_{ij3}), \tag{9}$$

where

$$x_{ij1}=\frac{1}{l}\sum_{k=1}^{l}x_{ij1}^k,\quad x_{ij2}=\frac{1}{l}\sum_{k=1}^{l}x_{ij2}^k,\quad x_{ij3}=\frac{1}{l}\sum_{k=1}^{l}x_{ij3}^k.$$

Step 2. Normalize the fuzzy group decision matrix
The fuzzy group decision matrix $\tilde{X}$ can be converted into a normalized fuzzy decision matrix $\tilde{R}=[\tilde{r}_{ij}]_{m\times n}$ using the vector normalization method:

$$\tilde{r}_{ij}=(r_{ij1},r_{ij2},r_{ij3})=\left(\frac{x_{ij1}}{x_{ij3}^*},\frac{x_{ij2}}{x_{ij3}^*},\frac{x_{ij3}}{x_{ij3}^*}\right),$$
$$x_{ij3}^*=\sqrt{\sum_{i=1}^{m}x_{ij3}^2}. \tag{10}$$

The normalization method adopted is to preserve the property that the ranges of normalized triangular fuzzy numbers belong to [0, 1].

Step 3. Construct the weighted fuzzy group decision matrix
Considering the different importance of each criterion, the weighted normalized fuzzy decision matrix $\tilde{R}'=\left[\tilde{r}'_{ij}\right]_{m\times n}$ can be constructed by the following equation:

$$\tilde{r}'_{ij}=\left(r'_{ij1},r'_{ij2},r'_{ij3}\right)=\overline{w}_j\otimes\tilde{r}_{ij}=(\overline{w}_jr_{ij1},\overline{w}_jr_{ij2},\overline{w}_jr_{ij3}) \tag{11}$$

where $\overline{w}_j$ are the weights of criteria, expressing the relative importance of criteria as computed by using the 2-tuple DEMATEL approach.

Step 4. The ratio system
For optimization, the assessments of decision makers are added in case of maximization and subtracted in case of minimization for each alternative:

$$\tilde{y}_i=\ \oplus_{j=1}^{g}\tilde{x}'_{ij}\ominus\ \oplus_{j=g+1}^{n}\tilde{x}'_{ij}, \tag{12}$$

where $i=1,2,\ldots,g$ are the criteria to be maximized; $i=g+1,g+2,\ldots,n$ are the criteria to be minimized; $\tilde{y}_i$ is the overall assessment of alternative A_i with respect to all criteria.

Step 5. The reference point approach
The reference point theory is based on the weighted normalized fuzzy decision matrix $\tilde{R}'=\left[\tilde{r}'_{ij}\right]_{m\times n}$ obtained by Eq. (11), whereby a maximal objective reference point (MORP) is also deduced. Since the elements $\tilde{r}'_{ij},\forall i,j$ are normalized positive triangular fuzzy numbers which belong to the closed interval [0, 1], we can define the fuzzy MORP as $\tilde{r}_j^*=(1,1,1)$ and $\tilde{r}_j^*=(0,0,0)$ for benefit and cost criteria, respectively. Then, it comes to the distance matrix $D=\left[d_{ij}\right]_{m\times n}$ by the following equation:

$$d_{ij}\ =d\left(\tilde{r}'_{ij},\tilde{r}_j^*\right)=\sqrt{\frac{1}{3}\left[\left(r'_{ij1}-r_{j1}^*\right)^2+\left(r'_{ij2}-r_{j2}^*\right)^2+\left(r'_{ij3}-r_{j3}^*\right)^2\right]}, \tag{13}$$

where the distance d_{ij} shows the gap of alternative A_i in the jth criterion C_j. The distance of each alternative from fuzzy MORP can be calculated by using the following equation:

$$d_i=\max_j d_{ij}. \tag{14}$$

In this study, we set the fuzzy MORP as the positive-ideal level in contrast to the traditional MULTIMOORA method, which selects

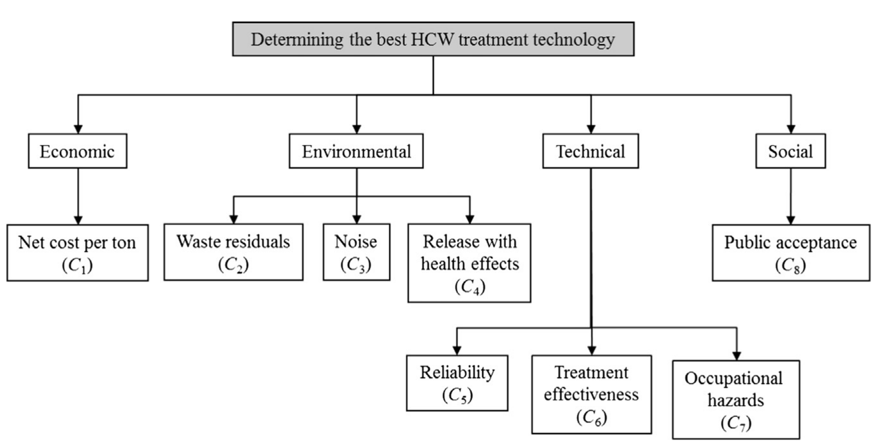

Fig. 2. Hierarchical structure of the considered problem.

the highest corresponding co-ordinate of the alternative as the MORP. This definition can avoid "choose the best among inferior options or alternatives" and thus, is more appropriate for the selection of HCW treatment technologies in the real-world.

Step 6. The full multiplicative form

The overall utility of the ith alternative can be expressed as a triangular fuzzy number by employing the following equation:

$$\tilde{u}_i = \tilde{a}_i \oslash \tilde{b}_i, \tag{15}$$

where $\tilde{a}_i = \otimes_{j=1}^{g} \tilde{x}'_{ij}$ denotes the product of criteria of the ith alternative to be maximized with $g = 1, 2, ..., n$ being the number of criteria to be maximized and where $\tilde{b}_i = \otimes_{j=g+1}^{n} \tilde{x}'_{ij}$ denotes the product of criteria of the ith alternative to be minimized with $n{-}g$ being the number of criteria to be minimized.

Step 7. Rank the alternatives

Rank the alternatives by sorting the values $\tilde{y}_i$ and $\tilde{u}_i$ for $i=1, 2, \ldots, m$ in decreasing order according to the point that divides the triangular fuzzy number into two equal areas [44], and the values d_i for $i=1, 2, \ldots, m$ in increasing order. Finally, the ranking order of all the alternatives can be determined based on the three ranking lists obtained, referring to the dominance theory [45].

4. Empirical example

4.1. Implementation

In this section, an empirical study conducted in Shanghai, China is presented to illustrate the application of the proposed hybrid decision making model to HCW treatment technology selection in the presence of interdependence among criteria. Shanghai is one of the largest cities in China, with a population of over 23 million people dispersed in 16 different districts and 1 county. It is reported that the amount of wastes collected and processed at the incineration plant in Shanghai has steadily increased in recent years due to the training efforts and the effect of the regulations [4]. Thus, the capacities of the existing incineration plants are insufficient to incinerate all the medical wastes generated in Shanghai. Through interviewing the experts from environmental protection bureau and the company that is responsible for collecting the HCWs in Shanghai, we reviewed and analyzed the HCW treatment technologies currently used in Shanghai, and discussed the problems encountered in HCW management. After preliminary screening, four possible treatment technologies have been determined for the disposal of medical wastes in Shanghai, namely, incineration (A_1), steam sterilization (A_2), microwave (A_3) and landfill (A_4).

Many quantitative and qualitative factors should be taken into consideration in determining the most preferred HCW treatment technology. As a result of literature review and experts interview, economic, environmental, technical and social dimensions are determined. Several relevant criteria corresponding to these dimensions are also identified in order to conduct a comprehensive evaluation of the treatment alternatives. The hierarchical structure of the problem comprising four evaluation dimensions and eight criteria is shown in Fig. 2.

In this paper, the influential weights of criteria and the ratings of alternatives regarding qualitative criteria are represented as linguistic variables. The decision makers used the linguistic term set S ranging from "Absolutely no influence (AN)" to "Very high influence (VH)" to evaluate the direct influence among criteria, and used the linguistic variables provided in Table 2 to determine the ratings of alternatives with respect to various criteria. The evaluation is conducted by an expert committee of five decision makers, DM_1, DM_2, DM_3, DM_4 and DM_5, which consists of two professional environmental engineers, two professors of industrial engineering, and a technical advisor specialized in waste management. A questionnaire is prepared concerning the evaluation criteria and the HCW treatment technologies, and the experts are asked to provide their opinions on the interrelationship between criteria and the ratings with respect to each criterion.

The data was gathered by informing the expert team on the purpose of the study first. An overview of each of the dimensions, clearly defining all the criteria, was provided and then each expert was given a 8×8 linguistic scale direct-influence matrix for comparison of the eight selection criteria. The diagonal elements of the direct-influence matrix were assigned a "NA" value. The remaining portions of the matrix were left blank to be filled in by the experts. To acquire the assessments of the experts on the four alternative treatment technologies, the linguistic scales used were defined according to the questionnaire answered by all decision makers. Triangular fuzzy numbers are chosen, since they are intuitive to decision makers. To elicit the membership functions from the experts, questions similar to this were asked: "What is the membership degree of 1 in 'Medium'?" It has to be noted that some published papers, technical reports, and regulations regarding HCW treatment technologies have been provided to the experts for them assess the influence between criteria and the performance of alternatives accurately. The linguistic evaluations collected from the five decision makers are summarized in Tables 3 and 4.

In what follows, we utilize the proposed hybrid MCDM model to determine the best HCW treatment alternative. The 2-tuple DEMATEL technique is first used to analyze the interrelationships among the eight evaluation criteria. First, the group direct-influence matrix $\tilde{Z} = [\tilde{z}_{ij}]_{8\times8}$ for the criteria is obtained as shown in Table A1 (see Appendix). Next, the normalized direct-influence matrix $X = [x_{ij}]_{8\times8}$ for the criteria is calculated by Eqs. (2) and (3) and shown in Table A2. Third, the total-influence matrix $T = [t_{ij}]_{8\times8}$ for the criteria are calculated based on Eq. (4). The results are represented in Table A3. Then, the INM of the given application can be constructed by using the vectors $\mathbf{r}$ and $\mathbf{c}$ in the

Table 3
Initial direct-influence matrices provided by the five decision makers.

Criteria	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
C_1	–	H,M,M,H,VH	H,L,M,L,H	VH,L,M,H,VH	L,L,M,H,L	M,L,M,AN,L	AN,L,AN,L,M	AN,AN,M,L,AN
C_2	AN,L,AN,AN,L	–	L,L,M,L,L	H,L,M,L,VH	L,L,M,L,AN	H,VH,M,H,VH	H,H,H,H,H	VH,VH,H,H,VH
C_3	AN,AN,L,L,L	AN,AN,AN,AN,AN	–	AN,AN,AN,AN,AN	L,L,AN,AN,AN	L,L,M,L,L	H,VH,M,H,M	VH,VH,M,H,VH
C_4	M,L,M,H,L	AN,L,M,L,AN	L,L,AN,L,L	–	M,L,AN,AN,L	M,L,M,L,M	VH,VH,H,VH,VH	H,VH,M,H,VH
C_5	VH,L,M,H,VH	H,VH,VH,H,VH	L,L,M,M,M	H,VH,M,L,L	–	H,H,M,H,VH	M,M,M,M,H	L,L,M,AN,L
C_6	L,L,M,L,M	VH,VH,VH,VH,VH	L,L,H,H,M	M,H,M,H,H	M,L,M,L,M	–	H,H,M,H,H	M,H,M,H,H
C_7	H,H,M,H,M	L,L,M,AN,L	AN,L,AN,AN,AN	L,L,AN,L,L	L,L,L,L,AN	M,L,M,L,L	–	L,L,L,H,L
C_8	H,H,H,M,H	L,L,AN,M,L	L,L,L,L,AN	L,M,M,M,L	L,M,M,L,L	H,VH,M,H,VH	M,L,M,L,L	–

Table 4
Linguistic assessments of alternatives provided by the five decision makers.

Decision makers	Alternatives	Criteria							
		C_1 (Min)	C_2 (Min)	C_3 (Min)	C_4 (Min)	C_5 (Max)	C_6 (Max)	C_7 (Min)	C_8 (Max)
DM_1	A_1	VH	ML	MH	VH	H	VH	ML	L
	A_2	ML	VL	M	ML	H	MH	VL	MH
	A_3	MH	L	ML	L	M	H	L	M
	A_4	ML	H	VL	MH	L	VL	MH	VL
DM_2	A_1	VH	L	VH	H	VH	H	L	L
	A_2	M	L	ML	L	VH	MH	L	H
	A_3	M	L	ML	L	M	M	ML	MH
	A_4	L	VH	VL	H	ML	L	H	VL
DM_3	A_1	H	L	H	MH	VH	H	ML	L
	A_2	M	ML	L	L	MH	VH	M	H
	A_3	M	VL	L	L	M	M	M	M
	A_4	L	VH	ML	H	MH	VL	L	VL
DM_4	A_1	VH	ML	H	VH	H	MH	M	VL
	A_2	M	L	L	M	M	M	H	M
	A_3	M	L	M	L	M	H	H	H
	A_4	L	H	M	MH	H	L	M	VL
DM_5	A_1	VH	M	M	MH	VH	H	M	VL
	A_2	ML	L	L	ML	MH	MH	VL	H
	A_3	H	L	M	L	M	M	M	MH
	A_4	ML	MH	ML	H	M	L	MH	L

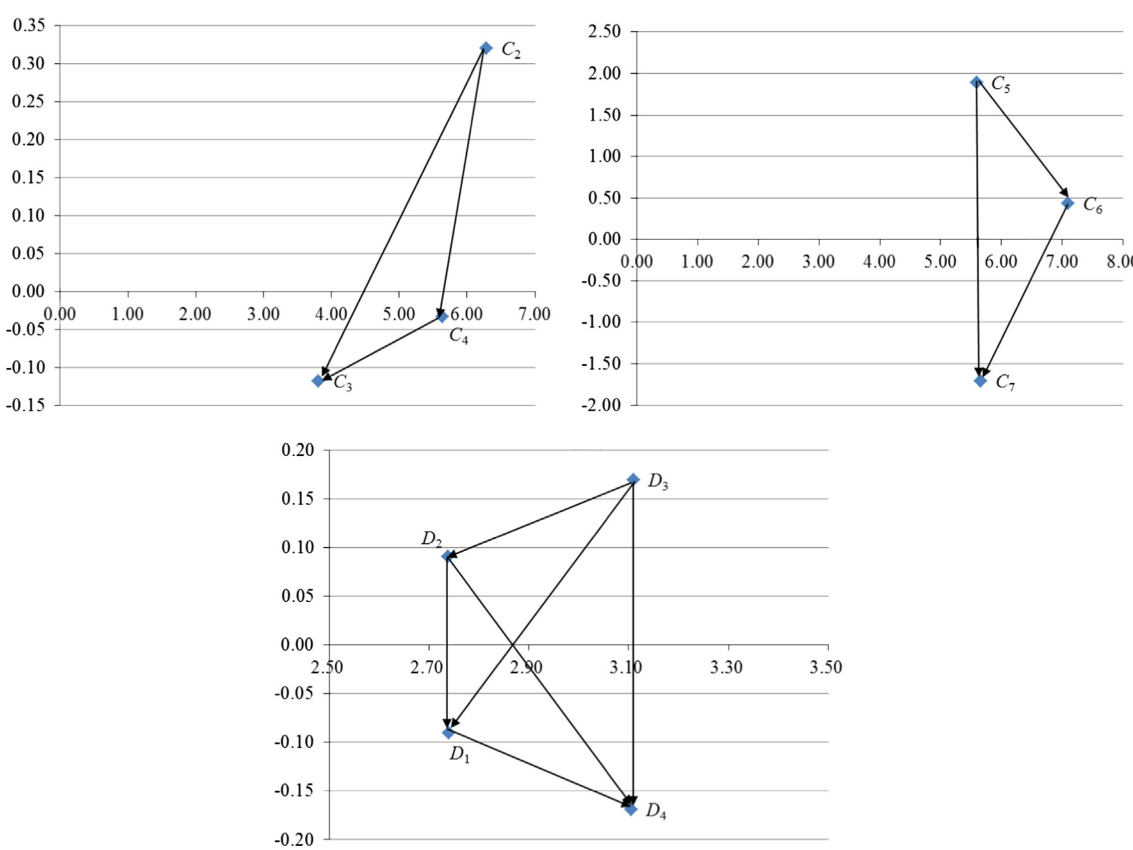

Fig. 3. Influential relation map among the dimensions and criteria.

total-influence matrix T, as expressed in Fig. 3. Finally, by using Eqs. (7) and (8), we can calculate the influence weights (global weights) and the normalized weights for all the criteria; the results are shown in Table 5.

After calculating the influence weights for the criteria by adopting the 2-tuple DEMATEL approach, the fuzzy MULTIMOORA method is applied thereafter to determine the ranking priorities of the alternative HCW treatment technologies. Quantifying by corresponding fuzzy numbers, the linguistic evaluations of decision makers are aggregated using Eq. (9) and the fuzzy group decision matrix $\tilde{X} = [\tilde{x}_{ij}]_{4\times8}$ obtained is presented in Table A4 (see Appendix). Then the normalized fuzzy decision matrix $\tilde{R} = [\tilde{r}_{ij}]_{4\times8}$ and the weighted normalized fuzzy decision

matrix $\tilde{R}' = \left[\tilde{r}'_{ij}\right]_{4\times8}$ are constructed as given in Tables A5 and A6 by employing Eqs. (10) and (11). Afterward, the ranking indices $\tilde{y}_i$, d_i and $\tilde{u}_i$ for $i=1, 2, \ldots, m$ are computed by utilizing Eqs. (13) and (15) and the final ranking order of all the alternatives can be determined according to the dominance theory [46]. The results of calculations are tabulated in Table 6. The ranking sequence suggests that the HCW treatment technology A_2 is the top ranking choice, followed by alternatives A_3, A_4 and A_1. Consequently, using the hybrid decision making model proposed in this study, the expert committee can recommend that steam sterilization (A_2) is the most appropriate technology for the considered HCW management problem in Shanghai.

4.2. Discussions

According to the above empirical study, the proposed hybrid MCDM model provides some important findings. First, in accordance with the results of 2-tuple DEMATEL (see Table 5), treatment effectiveness (C_6) is the most important criterion with influence weight of 0.152, and noise (C_3) is the least important one with influence weight of 0.082. In the environmental (D_2) dimension, the experts consider waste residuals (C_2) to be the most important criterion. In the technical (D_3) dimension, the experts think that treatment effectiveness (C_6) is the most crucial criterion. These findings reveal that the experts believe environmental (D_2) and technical (D_3) dimensions should not be overlooked by decision makers when selecting the best technology for the treatment of HCW.

Second, the modified 2-tuple DEMATEL method can also be utilized to understand the interrelationship among dimensions and criteria (cf. Fig. 3). The IRM shows that the environmental (D_2) and technical (D_3) dimensions have more influence over the other two dimensions. This finding means that decision makers should first improve these two dimensions because they are the most important relative to the other dimensions. Thus, the environmental and the technical dimensions can be regarded as the critical aspects for evaluating and improving the HCW treatment alternatives for the case study in Shanghai. In addition, with respect to the environmental (D_2) dimension, waste residuals (C_2) is the most influential criterion and should be improved upon first, followed by release with health effects (C_4) and noise (C_3). With respect to the technical (D_3) dimension, reliability (C_5) is the most influential criterion and should be improved upon first, followed by treatment effectiveness (C_6) and occupational hazards (C_7). As can be seen from Fig. 3, it also determines the social (D_4) dimension is being influenced most, that is, the social aspect in the four dimensions represents an important problem which should pay more attention to. Each of the evaluation dimensions and criteria identify the necessary behaviors for improving the HCW treatment technology selection of the waste management problem. Therefore, decision makers should evaluate all of the dimensions and criteria for the technology selection process in terms of Fig. 3.

Third, from the results obtained by fuzzy MULTIMOORA (see Table 6), the ranking order of the HCW disposal alternatives is $A_2 \succ A_3 \succ A_1 \succ A_4$, suggesting steam sterilization (A_2) as the most suitable HCW treatment technology. Steam sterilization is the best alternative treatment method since it minimizes the impact on the environment and demonstrates a commitment to public health. Non-incineration technologies, i.e., steam sterilization and microwave, are placed in the first and second rankings for the preferred waste treatment methods mainly due to the fact that they appear to emit fewer pollutants and generate non-hazardous residues [3]. While landfill is an economic alternative compared with other HCW treatment methods, it should only be used in a limited extent because of its adverse environmental and public health effects [46,47]. It is also concluded that like landfilling, incineration ranks after non-incineration technologies because of its high costs and the risks for the environment and public health [48]. Therefore, building a central steam sterilization plant can be considered as the most cost effective and appropriate solution from the view of environment and public health.

4.3. Comparisons

In addition, to illustrate the effectiveness of the proposed hybrid MCDM model for selecting HCW treatment technologies, we use the above case study to analyze some comparable methods, which include fuzzy TOPSIS [3] and fuzzy VIKOR [4]. Table 7 shows the ranking results of all the four HCW disposal alternatives as obtained utilizing these methods. As can be seen from Table 7, the rankings calculated by the proposed hybrid

Table 5
Influences among criteria and their relative weights.

Dimensions	Criteria	r	c	$r+c$	$r-c$	w_j	$\overline{w}_j$
D_1	C_1	2.730	2.891	5.621	−0.160	5.623	0.120
D_2	C_2	3.306	2.986	6.291	0.320	6.299	0.135
	C_3	1.848	1.965	3.813	−0.117	3.814	0.082
	C_4	2.800	2.833	5.634	−0.033	5.634	0.121
D_3	C_5	3.741	1.851	5.592	1.890	5.902	0.126
	C_6	3.768	3.333	7.101	0.434	7.114	0.152
	C_7	1.972	3.686	5.658	−1.714	5.912	0.127
D_4	C_8	2.892	3.512	6.404	−0.620	6.434	0.138

Table 7
Ranking comparisons.

Alternatives	Fuzzy VIKOR				Fuzzy TOPSIS			
	S_i	R_i	Q_i	Ranking	D_i^+	D_i^-	C_i^*	Ranking
A_1	0.502	0.121	0.606	3	0.635	0.537	0.458	3
A_2	0.159	0.057	0.000	1	0.368	0.836	0.694	1
A_3	0.342	0.126	0.509	2	0.484	0.730	0.601	2
A_4	0.789	0.152	1.000	4	0.838	0.341	0.289	4

Table 6
The ranking of alternatives according to fuzzy MULTIMOORA.

Alternatives	$\tilde{y}_i$	Ranking	d_i	Ranking	$\tilde{u}_i$	Ranking	Final ranking
A_1	(−0.195, −0.105, −0.01)	3	0.986	3	(23.1, 204.8, 3371.5)	3	3
A_2	(−0.047, 0.073, 0.178)	1	0.943	1	(1334.1, 23169.3, 941437.4)	1	1
A_3	(−0.106, 0.014, 0.129)	2	0.962	2	(433, 9344, 390858.2)	2	2
A_4	(−0.293, −0.212, −0.106)	4	0.993	4	(0.6, 15.7, 1598.6)	4	4

model are the same as those derived by the fuzzy TOPSIS and the fuzzy VIKOR methods. This demonstrates the validity of the proposed modeling scheme. Compared with the extant approaches for the selection of HCW treatment technologies, the model proposed in this study has the following advantages:

- The proposed model could tackle the complicated and interrelated relationships among dimensions and criteria and produce results that allow us to build a visual cause-and-effect diagram for improving the alternative HCW treatment technologies.
- Evaluation criteria of HCW disposal alternatives and their interdependent relationships are evaluated in a linguistic way rather than in precise numerical values. This enables the experts to express their judgments more realistically and makes the assessment easier to be carried out.
- Multiple and conflicting criteria including quantitative as well as qualitative can be taken into account and assessed during the HCW disposal method selection process. The proposed model is not limited to the eight evaluation criteria listed in the case study, but applicable to any number of criteria.
- With the proposed model, the priority ranking of alternative HCW disposal methods is determined by employing the MULTIMOORA, which is more applicability, potentiality and easy to implement in comparison other MCDM methods such as TOPSIS and VIKOR [49]. Hence, the proposed decision making framework can conduct robust evaluation of the HCW treatment technologies and thus is more suitable for real applications.

5. Conclusions

Selecting the appropriate treatment technology in HCW management is a difficult and restrained task for the municipal authorities especially in developing countries. In this paper, we proposed a hybrid MCDM model combining the 2-tuple DEMATEL and fuzzy MULTIMOORA methods to determine the best treatment technology in the HCW management system. The proposed model could handle the complex interactions and interdependences among dimensions and criteria and produce results that allow us to build a visible causal relationship diagram for evaluating the HCW disposal alternatives. We cannot only select the optimal treatment technology for HCW but also find how to improve the gaps to achieve the aspiration level for improving existing disposal alternatives. That is, the proposed model can avoid selecting the best among inferior alternatives.

An empirical study conducted in Shanghai, China was used to demonstrate the application of the proposed model to the HCW treatment technology selection problem. By using the modified 2-tuple DEMATEL technique, the criteria for evaluating HCW treatment alternatives are proved having interrelations and interdependence relationships. Though engineers have to take into account the effects of all factors when making decisions of HCW treatment technology selection, experts noted that the environmental and technical related criteria should be given the most important weights. As a result of the fuzzy MULTIMOORA method, alternative A_2 (steam sterilization) was found to be the most suitable HCW treatment technology, followed by the alternatives A_3, A_1 and A_4. The selected technologies agreed almost completely with those obtained by previous researches. It was validated that the proposed hybrid MCDM model is an effective tool in solving the complex HCW treatment technology selection problem with inter-dependent criteria and compromise alternatives.

In further research, the following directions are suggested. First, the objective weights of criteria are not considered in the developed model. The subjective weights are excessively dependent on experts' personal judgments, which may result in some errors or mistakes owning to lack of knowledge and data [50]. Thus, it is necessary to develop a new approach for HCW management which can take into account subjective and objective weights of criteria simultaneously. Second, fuzzy logic is integrated with the MULTIMOORA method in the proposed model to deal with the vagueness and ambiguity in decision making process. This, however, may produce a loss of information in the linguistic information processing since the computation results usually do not exactly match any of the initial linguistic terms. Hence, the combination with interval 2-tuple linguistic representation model [51] should be investigated in the future. Additionally, a great variety of MCDM methods have been developed to handle problems under different circumstances and fields of application [52]. However, to the best of our knowledge, only a few of them (i.e., VIKOR, TOPSIS and AHP) have been employed for decision making in HCW management systems. Therefore, in future, applying other methods (e.g., PROMETHEE, ELECTEREE and COPRAS, etc.) for the evaluation of HCW treatment technologies may have enormous chance of success.

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Appendix

See Tables A1–A6.

Table A1
The group direct-influence matrix $\tilde{Z}$.

Criteria	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
C_1	$(s_0, 0)$	$(s_3, -0.2)$	$(s_2, 0)$	$(s_3, -0.2)$	$(s_2, -0.4)$	$(s_1, 0.2)$	$(s_1, -0.2)$	$(s_1, -0.4)$
C_2	$(s_0, 0.4)$	$(s_0, 0)$	$(s_1, 0.2)$	$(s_2, 0.2)$	$(s_1, 0)$	$(s_3, 0.2)$	$(s_3, 0)$	$(s_4, -0.4)$
C_3	$(s_1, -0.4)$	$(s_0, 0)$	$(s_0, 0)$	$(s_0, 0)$	$(s_0, 0.4)$	$(s_1, 0.2)$	$(s_3, -0.2)$	$(s_3, 0.4)$
C_4	$(s_2, -0.2)$	$(s_1, -0.2)$	$(s_1, -0.2)$	$(s_0, 0)$	$(s_1, -0.2)$	$(s_2, -0.4)$	$(s_4, -0.2)$	$(s_3, 0.2)$
C_5	$(s_3, -0.2)$	$(s_4, -0.4)$	$(s_2, -0.4)$	$(s_2, 0.2)$	$(s_0, 0)$	$(s_3, 0)$	$(s_2, 0.2)$	$(s_1, 0)$
C_6	$(s_1, 0.4)$	$(s_4, 0)$	$(s_2, 0)$	$(s_3, -0.4)$	$(s_2, -0.4)$	$(s_0, 0)$	$(s_3, -0.2)$	$(s_3, -0.4)$
C_7	$(s_3, -0.4)$	$(s_1, 0)$	$(s_0, 0.2)$	$(s_1, -0.2)$	$(s_1, -0.2)$	$(s_1, 0.4)$	$(s_0, 0)$	$(s_1, 0.4)$
C_8	$(s_3, -0.2)$	$(s_1, 0)$	$(s_1, -0.2)$	$(s_2, -0.4)$	$(s_1, 0.4)$	$(s_3, 0.2)$	$(s_1, 0.4)$	$(s_0, 0)$

Table A2
The normalized direct-influence matrix X.

Criteria	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
C_1	0.000	0.165	0.118	0.165	0.094	0.071	0.047	0.035
C_2	0.024	0.000	0.071	0.129	0.059	0.188	0.176	0.212
C_3	0.035	0.000	0.000	0.000	0.024	0.071	0.165	0.200
C_4	0.106	0.047	0.047	0.000	0.047	0.094	0.224	0.188
C_5	0.165	0.212	0.094	0.129	0.000	0.176	0.129	0.059
C_6	0.082	0.235	0.118	0.153	0.094	0.000	0.165	0.153
C_7	0.153	0.059	0.012	0.047	0.047	0.082	0.000	0.082
C_8	0.165	0.059	0.047	0.094	0.082	0.188	0.082	0.000

Table A3
The total-influence matrix T.

Criteria	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
C_1	0.254	0.410	0.284	0.402	0.251	0.369	0.392	0.367
C_2	0.353	0.326	0.276	0.425	0.261	0.534	0.560	0.571
C_3	0.225	0.182	0.115	0.173	0.140	0.271	0.359	0.381
C_4	0.377	0.320	0.222	0.262	0.220	0.394	0.526	0.480
C_5	0.495	0.562	0.333	0.475	0.232	0.568	0.577	0.499
C_6	0.436	0.567	0.346	0.487	0.316	0.423	0.610	0.583
C_7	0.327	0.261	0.147	0.241	0.171	0.293	0.234	0.298
C_8	0.423	0.359	0.241	0.369	0.259	0.481	0.428	0.333

Table A4
The fuzzy group decision matrix $\tilde{X}$.

	A_1	A_2	A_3	A_4
C_1	(8.6, 9.8, 10)	(2.2, 4.2, 6.2)	(4.2, 6.2, 8.0)	(1.0, 2.4, 3.8)
C_2	(1.4, 3.0, 4.6)	(1.2, 2.4, 3.8)	(0.8, 1.6, 2.6)	(7.4, 9.0, 9.8)
C_3	(6.2, 8.0, 9.2)	(1.4, 2.8, 4.2)	(1.8, 3.6, 5.4)	(1, 2.2.0, 3.8)
C_4	(7.0, 8.6, 9.6)	(1.4, 3.0, 4.6)	(1.0, 2.0, 3.0)	(6.2, 8.2, 9.6)
C_5	(8.2, 9.6, 10)	(5.8, 7.6, 9.0)	(3.0, 5.0, 7.0)	(3.4, 5.2, 6.8)
C_6	(7.0, 8.8, 9.8)	(5.4, 7.2, 8.8)	(4.6, 6.6, 8.2)	(0.6, 1.2, 2.2)
C_7	(1.8, 3.6, 5.4)	(2.2, 3.2, 4.4)	(3.0, 4.8, 6.4)	(4.2, 6.0, 7.6)
C_8	(0.6, 1.2, 2.2)	(5.8, 7.8, 9.2)	(4.6, 6.6, 8.4)	(0.2, 0.4, 1.4)

Table A5
The normalized fuzzy decision matrix $\tilde{R}$.

	A_1	A_2	A_3	A_4
C_1	(0.584, 0.665, 0.679)	(0.149, 0.285, 0.421)	(0.285, 0.421, 0.543)	(0.068, 0.163, 0.258)
C_2	(0.119, 0.255, 0.391)	(0.102, 0.204, 0.323)	(0.068, 0.136, 0.221)	(0.629, 0.765, 0.833)
C_3	(0.513, 0.662, 0.762)	(0.116, 0.232, 0.348)	(0.149, 0.298, 0.447)	(0.083, 0.182, 0.315)
C_4	(0.478, 0.587, 0.656)	(0.096, 0.205, 0.314)	(0.068, 0.137, 0.205)	(0.423, 0.56, 0.656)
C_5	(0.493, 0.578, 0.602)	(0.349, 0.457, 0.542)	(0.181, 0.301, 0.421)	(0.205, 0.313, 0.409)
C_6	(0.447, 0.562, 0.625)	(0.345, 0.459, 0.562)	(0.294, 0.421, 0.523)	(0.038, 0.077, 0.14)
C_7	(0.148, 0.297, 0.445)	(0.181, 0.264, 0.363)	(0.247, 0.396, 0.527)	(0.346, 0.494, 0.626)
C_8	(0.047, 0.094, 0.173)	(0.456, 0.613, 0.723)	(0.361, 0.519, 0.66)	(0.016, 0.031, 0.11)

Table A6
The weighted normalized fuzzy decision matrix $\tilde{R}'$.

	A_1	A_2	A_3	A_4
C_1	(0.070, 0.080, 0.082)	(0.018, 0.034, 0.051)	(0.034, 0.051, 0.065)	(0.008, 0.020, 0.031)
C_2	(0.016, 0.034, 0.053)	(0.014, 0.027, 0.044)	(0.009, 0.018, 0.030)	(0.085, 0.103, 0.112)
C_3	(0.042, 0.054, 0.062)	(0.009, 0.019, 0.028)	(0.012, 0.024, 0.036)	(0.007, 0.015, 0.026)
C_4	(0.058, 0.071, 0.079)	(0.012, 0.025, 0.038)	(0.008, 0.016, 0.025)	(0.051, 0.068, 0.079)
C_5	(0.062, 0.073, 0.076)	(0.044, 0.058, 0.068)	(0.023, 0.038, 0.053)	(0.026, 0.040, 0.052)
C_6	(0.068, 0.085, 0.095)	(0.052, 0.07, 0.085)	(0.045, 0.064, 0.080)	(0.006, 0.012, 0.021)
C_7	(0.019, 0.038, 0.056)	(0.023, 0.033, 0.046)	(0.031, 0.050, 0.067)	(0.044, 0.063, 0.079)
C_8	(0.006, 0.013, 0.024)	(0.063, 0.084, 0.100)	(0.050, 0.071, 0.091)	(0.002, 0.004, 0.015)

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